Research Effort and Economic Growth

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1 November 2021

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Abstract

Endogenous growth models based on micro-foundations predict that total factor productivity (TFP) growth is positively associated with effective research effort. We use macroeconomic-pooled time series-cross sectional data for the G7 countries from 2000 to 2017 to provide a robust estimate of this positive effect of research effort on TFP growth.

JEL Classifications O40, O47

Keywords TFP Growth, Research Efforts, Education, Human Capital, Useful Knowledge

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1. Introduction

Several generations of endogenous and semi-endogenous growth models, which are based on micro- foundation at the firm level e.g., Jones (2002), Jones and Kim (2018), and Bloom *et al.* (2020), model total factor productivity (TFP) growth rate as a function of effective research effort.[i] This relationship is a key mechanism to drive economic growth in such models. An important assumption underlying this mechanism is that the representative firm carries out innovations in order to compete. The innovations require investments in research and development. Research effort is the product of human capital and the number of people engaged in R&D activity.[ii] People acquire human capital by attending schools or taking up training, i.e., upskilling, hence investments in human capital. The time individuals use to attend schools or engage in training programs is the time spent out of the labor market. Therefore, when they are training to acquire human capital they are not involved in the production of output. The firms are heterogeneous. Each firm is a monopolistic competitor producing a particular product. To aggregate over firms in these models, we assume symmetry, whereby the firms choose the same starting values for their control variables, i.e., any one firm is representative of the rest. Simon Kuznets (1973, pp. 251) calls this process, the process of producing *useful knowledge*, which derived economic growth in developed countries *per se*.[iii]

Bloom *et al.* (2020), among others, explain the observed recent decline of TFP growth in developed countries despite the increase in the number of people engaged in research over time. They use *micro* data to argue that although the number of researchers and research intensity has increased, research productivity has declined, hence TFP growth declined. Their interpretation of this negative association is that research ideas have become hard to find. Dawson and Seater (2013) argue that the firm's level of TFP may fall because of the increase in the marginal tax rate and regulation. Coffey *et al.* (2020) use a completely different methodology and data to reach a similar conclusion for the U.S.

Endogenous growth models are highly parameterized. For example, Jones (2000) has at least 12 parameters. These models are typically, but not necessarily, calibrated rather than estimated. Some of the parameters used in calibrating the models are estimates found in other microeconomic studies; others are theoretically based values used along with sensitivity analysis. As far as we know, there are no estimates of the parameters underlying the relationship between TFP growth and research effort. The objective of this paper is to estimate these parameters for the G7 countries over a sample from 2000 to 2017, i.e., pooled time-series – cross section data, using a variety of estimators. Furthermore, we use two different measures of TFP, one is the aggregate TFP and the other is a *market economy* measure of TFP, which excludes the public sector and the services sectors, where output is usually hard to measure. See the data appendix. The evidence shows that the market measure of TFP fits the model better than the aggregate TFP measure does.

In the next section, we present the model. Section (3) presents the data, estimation, and the results. Section (4) is a summary.

2. The Model

The typical aggregate equation that links technical progress growth to research effort in the endogenous growth literature is:

$$\frac{\dot{A}}{A} = H \,, \qquad (1)$$

where A is technical progress, the dot on top of it is the rate of change, thus $\frac{\dot{A}}{A}$ is the percentage growth rate, which is proportional to the level of effective research effort H. Effective research effort is a function of human capital and the number of researchers.

For estimation purpose, we assume a non-linear function for H,

$$H = h^{\alpha} L^{\beta} e^{u}. \qquad (2)$$

Hence, H is the product of the *level* of the stock of human capital h and the number of people engaged in research L; α and β are the shares. The share of human capital isα, the share of researchers is β, and u is an error term with all classical assumptions. Next, we estimate these shares.

3. Estimation

To estimate the model, we test the restriction $\alpha + \beta = 1$. The fit of the model improves if the restriction is valid and accepted by the data. Replace β in equation (2) with $1 - \alpha$, Substitute (2) in (1), log-linearizing, and rearranging the terms yields the estimable equation:

$$\Delta lnA_t - lnL_t = \alpha[lnh_t - lnL_t] + u_t, \qquad (3)$$

hence, the parameter α is an elasticity.

We begin by plotting the data we are using for estimation. Figure (1) plots the human capital data. Visually, the data have positive but changing trends over time. Figure (2) plots the number of researchers, which varies across the G7. Canada has volatile data with a positive trend, which seems to have flattened from 2011 onward. France, Germany, and Italy have positive rising trends. Japan has a volatile data and no trend. The U.K. data have a positive trend up to 2006, flattens thereafter, to 2013 then starts rising slowly again. The U.S. data have a positive trend, albeit volatile. In terms of magnitude, however, there are far more researchers in Japan and the U.S. than in any other country. Figure (3) plots the two measures of TFP, an *aggregate* TFP and a *market* measure (see the data appendix for details). The two measures of TFP are significantly different. The market measure excludes the government public institutions and other services sectors, where output is "hard to measure," hence; it is more reliable than aggregate TFP. Figure (4) is a scatter plot of TFP growth rate per researcher, *aggregate measure*, and human capital per researcher, i.e., the dependent ($\Delta lnA_t - lnL_t$) and the independent $[lnh_t - lnL_t]$ variable in equation (3). [iv] We expect the regressions to reflect these high correlations.

The estimation of equation (3) is straightforward; however, there are two estimation problems, which require remedies. First, the time series sample from 2000 to 2017 is short, hence a small sample bias. Second is the potential endogeneity problem, human capital and the number of researchers, i.e., single-equation bias problem. Investments in human capital and in the number of researchers are endogenous decisions.

To resolve the small sample problem we estimate a pooled times series – cross sectional data for the G7 from 2000 to 2017. We remedy the endogeneity problem by using an Instrumental Variable estimator (IV). For robustness, we use EGLS and the Generalized Method of Moments (GMM). The key advantage of GMM is that it requires specification only of a certain moment rather than the full density. The drawback is that GMM may not make efficient use of all the information in the sample. For this reason, we use, in addition, the Two-Stage Least Squares (2SLS) estimator. For proof of the asymptotic efficiency see Wooldridge (2001, p. 96-97). For each of the IV estimators, we use two different sets of instruments. The first set includes a constant term, and lagged values of the regressor. The second set of instruments includes the population's distribution, i.e., ages 15-19 through to 60-64 years. These instruments are consistent with the Life-Cycle Hypothesis, whereby investments in human capital and in the number of researchers increase with age, level up at a certain age, and then decline, as people get older. We test the instruments for relevance, i.e., identified, highly correlated with the regressor, uncorrelated with the error term, and strictly exogenous as required.

3.1 Estimation Using the Aggregate TFP Measure

To deal with both the small sample and the endogeneity problems jointly, we estimate a fixed-effect pooled time series – cross sector equation using EGLS, 2SLS and GMM. The equation, fixed-effect model, is given by:[v]

$$\Delta ln\,(A_{it}) - ln(L_{it}) = \alpha[(ln(h_{it}) - ln(L_{it})] + u_{it}, \qquad (4)$$

where, $u_{it} = \eta_i + \nu_{it}$ and the subscript $i = 1 \ldots 7$, G7 countries.

Table (1) reports the EGLS estimates as a benchmark for comparison with the 2SLS and GMM estimates. Two estimates are reported, one is in the top row of the table, where we interpret α as an *average* across all the G7 countries because it does not vary across countries, and the other is where α varies across countries, e.g., α_i, where $i = 1 \ldots 7$, G7 countries. The average α estimate is 1.15, which statistically significantly different from zero. The Wald P-value indicates that we can reject the null hypothesis that the average $\alpha = 1$, therefore, average $\alpha > 1$.

Thus, the implied average β in this case is -0.15. The fit is high. The estimates are White, cross-section standard errors & covariance with degrees of freedom corrections. We interpret α to mean that, on *average*, a one percent increase in the level of human capital per researcher increases the growth rate of TFP (aggregate measure) per researcher by 1.15 percent. Hence, a 1 percent increase in research effort increases TFP growth by more than 1 percent on average. The negative implied βseems to be consistent with Bloom's *et al* (2020) interpretation that the increase in the number of researchers reduces TFP growth on average.

When α varies across countries, the estimated α_i are significantly different from zero, except for Japan. The Wald P-values indicate that α is insignificantly different from one in Canada, the U.K. and the U.S. only (i.e., $\alpha = 1$), therefore, the implied β's are zero. For France and Italy, the α's >1, hence the implied β's are -0.21 and -0.20, respectively. Germany's α is 0.67, hence β is 0.33.

We report the estimates of α using 2SLS in tables (2) and (3). Table (2) reports the estimates using lagged values of the regressor in equation (3) as instruments. The estimated average α is 1.11, slightly smaller than the EGLS estimate above, and significantly different from zero. The Wald P value of 0.2290 is high, thus we cannot reject the hypothesis that the average α is one, which is different from the EGLS estimate. Thus, the average implied $\beta$is zero. The J stat P value is 0.5727; therefore, we cannot reject the instruments' over-identification restrictions. For α_i, all the estimates are significantly different from zero, except for Japan. However, α for Canada and the U.K., just like the EGLS estimates, is insignificantly different from one as the Wald P values indicate. Thus, the implied β's are zero. France's α is probably equal one at the 10 percent level only. For Germany, Italy, and the U.S., α is statistically different from one.

Table (3) reports the 2SLS estimates using a different set of instruments. We argued before that the population distribution, as an instrument, is consistent with the Life-Cycle hypothesis. On average, the estimated α is 1.15, which is identical to the EGLS estimate in table (1). The Wald P value indicates that it is statistically different from one, therefore β is -0.15 on average.

For α_i, all estimates are significantly different from zero, except for Japan. However, the Wald P values indicate that only Canada, the U.K. and the U.S. are statistically significantly indifferent from one, i.e. $\alpha = 1$. France, Germany, and Italy have estimates of α>1. These results are almost identical to those of EGLS reported in table (1). The fit is high. The estimated standard errors are White cross-section and degrees of freedom corrected. The J P value indicates that we cannot reject the instruments' over-identification restrictions.

Table (4) and (5) report the GMM estimates. Table (4) reports the GMM estimates when the instruments are just the lags of the regressor and a constant term. In the first row, the average α is 1.03, statistically significant, and statistically insignificant from one as indicated by the Wald P value. This is similar to the 2SLS estimate, where the same instruments were used. The J statistic P value indicates that we cannot reject the instrument's over-identification restrictions. For α_i, the parameter estimates are identical to those from 2SLS reported earlier. They are also statistically equivalent.

Table (5) reports the GMM estimates using the second set of instruments, the population distribution. On average, α is different from the 2SLS estimate; the GMM estimate is 1.05, significant; however, the Wald P value indicates that the GMM estimate is insignificantly different from one while the 2SLS was different from one. Overall, the average estimates of α using different estimators and different instruments are close in magnitude and the country estimates of α are identical in 2SLS and GMM when the instruments are the same. All estimates of α are significant, and in a few cases were not different from one. The regressions then reflect the scatter plot in Figure (4) remarkably well.

Finally, we estimate the same equation using the same estimators but with a different measure of TFP, which we believe is more consistent with growth theory because it measures *market* productivity more closely. Aggregate TFP data may not be an appropriate measure of productivity since the aggregates include government and services industries whose productivity levels are imprecisely measured because outputs are hard to measure in these sectors. For this reason, we re-estimate the model using a *market-economy* measure of TFP. The EUKLEMS data set includes data for TFP excluding a number of sectors of the total economy, Stehrer *et al.* (2019). The data set excludes Canada (see the data appendix).

3.4. Estimation Using a Market TFP Measure

Figure (5) is a scatter plot of TFP growth rate per researcher, *market measure*, and human capital per researcher. The fit is much better than figure (4), and it improved greatly for Japan.[vi] We use EGLS, 2SLS, and GMM to estimate the fixed-effect model with the G7 countries pooled time series – cross section data from 2000 to 2017. The results are reported in tables (6), (7), (8), (9), and (10). In general, we obtain very similar results across estimators. For *average* α, the IV estimators give identical results, 1.11, 1.15, 1.03, and 1.05 for 2SLS with lag instruments, 2SLS with population distribution instruments, GMM with lag instruments, and GMM with population distribution instruments respectively. The EGLS estimates are insignificantly different, 1.17 and 1.15 respectively. Hence, we interpret these elasticities the same way. On average across the G6 (G7 less Canada), a one percent increase in research effort increases TFP growth by 1 or slightly more than 1 percent.

For α_i, just like the previous set of results of the aggregate TFP measure, the parameter estimates of 2SLS and GMM are identical when the instruments are the same. All estimated parameters are statistically significantly different from zero, except Japan although the magnitude of its α is larger in magnitude than before. The diagnostic statistics are similar too. The interpretation remains unchanged. The increase in research effort by one percent increases TFP growth by more than one percent, and the increase in the number of researchers have been associated with declining TFP growth.

Table (11) and (12) are summaries of the parameter estimates. The overall results indicate that (1) the increase in research effort increases TFP growth. The elasticity is between 1 and slightly greater than 1. The estimates are robust to estimators and the fit of the equation is high, which supports the theory and the specification of the model. (2) The implied responsiveness of TFP growth to the number of researchers is negative to zero. This result is consistent with the findings of Bloom *et al.* (2002), which may indicate that the increase in the number of researchers has not generated useful knowledge. (3) The market measure of TFP fits the model better than the aggregate measure because it measures output more precisely by excluding in the services and government sectors. (4) Japan is the only country in the G7 whose TFP growth is different. The model does not fit the Japanese data and the parameter estimate is insignificantly different from zero. (5) The differences in the magnitudes of the responsiveness of TFP growth to research effort across the G7 vary between Canada, the U.K., and the U.S. on one side and the European countries on the other. The Anglophone countries' α is ≈ 1 (implied $\beta = 0$) while the European countries' $\alpha > 1$ (implied $\beta < 0$). In summary, the macro evidence supports the micro theory strongly for the G7 data.

5. Summary

We examine the prediction of the micro-founded endogenous growth theory that *TFP growth* is proportional to the *level* of effective research effort. A two-equation representation of this key relationship is provided, whereby the effective research effort is assumed a non-linear product of the stock of human capital and the number of researchers in the G7 countries.

We use macro-level data and a number of estimators, e.g., EGLS and two IV estimators, namely 2SLS and GMM, to estimate a fixed-effect model with a panel of pooled time series – cross section data from 2000 to 2017 for the G7 countries. We show that there is a significant relationship between the *level* of research effort and *aggregate* TFP *growth*. *On average*, the estimated elasticity of research effort with respect to TFP growth is either one or slightly higher than one, however, varies across the G7. Japan is the only country in the G7, where research effort does not have a significant effect on TFP growth. There is also a noticeable difference in the magnitude of the parameter estimates in Canada, the U.K. and the U.S. on one hand, and the European countries France, Germany, and Italy on the other. The formers estimates are insignificantly different from one, while the European countries estimates are greater than one. The European countries' data fit of the model is better too. However, on average, for the G7, a 1 percent increase in research effort increases TFP growth per researcher by 1.096 percent.

In addition to the aggregate TFP measure, we tested the same relationship using a *market measure* of TFP, which excludes public sectors and services sectors, where the measurement of output is imprecise, and showed that the relationship between TFP growth and effective research effort is even stronger. The results also indicate that the increase in research effort increases TFP growth and the fit of the model improved for all countries including Japan, which is interesting. It suggests that the relationship between research effort and TFP growth is strongest in the market *per se*. The average elasticity is 1.18 percent. If we take all the parameter estimates across the G7 countries using *aggregate and market* TFP, the average estimate of the elasticity of research effort with respect to TFP growth is 1.14 percent.

The empirical evidence, which we provided is supportive of the theoretical endogenous growth mechanism. Economic growth is attributed to TFP growth, which increases by more than one to one with research effort. Precisely, research effort is the level of human capital per researcher. Therefore, the estimated parameters reported in this paper are useful for calibrating endogenous growth models. From a policy perspective, whether it is public or private, the increase in the number of researchers is not, by itself, the driver of research effort. The increase in the number of researchers can have a negative impact unless it is combined with high levels of human capital. Emphasis on the development of human capital is crucial for TFP growth. Human capital would increase with education, training, and upskilling programs albeit it is a lengthy and complex process. Increasing average years of schooling per se does not guarantee the increase of the level of human capital. The same number of years of schooling in developing countries yields different outcomes in developed countries than developed countries. The outcomes vary across developed countries too, and within every developed country. The quality of human capital is most important for growth. However, measuring the quality of education and adjusting the quality of human capital are not straightforward; see Razzak and Laabas (2016). Future research needed in this area. In addition, future research should attempt to examine the effect of this endogenous TFP theory on real GDP per capita and most importantly on the real GDP per capita differentials.

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Table (1) – EGLS Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 7
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on an Aggregate Measure TFP

	Estimate	P value	Wald	R^2	DW	σ	Implied β
$\boldsymbol{\alpha}$	1.15	(0.0000)	(0.0001)	0.98	2.11	0.11	-0.15
$\boldsymbol{\alpha_i}$							
Canada	0.96	(0.0000)	(0.9391)				0.00
France	1.21	(0.0000)	(0.0025)				-0.21
Germany	0.67	(0.0000)	((0.0018)				0.33
Italy	1.20	(0.0000)	(0.0000)				-0.20
Japan	0.26	(0.7786)	NA				NA
U.K.	1.35	(0.0000)	(0.2283)				0.00
U.S.	0.84	(0.0000)	(0.4065)				0.00
$\bar{R}^2$	0.99						
DW	2.29						
σ	0.11						

- $A_t$is aggregate TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- Linear estimation after one –step-weighting matrix is used. White cross section standard errors and covariance with degree of freedom correction.
- Wald tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- Japan's estimate is statistically equal to zero.

Table (2) – 2SLS Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 7
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on an Aggregate Measure TFP
The instruments are a constant and two lags of regressor

	Estimate	P value	Wald	R^2	DW	J P value	σ	Implied β
$\boldsymbol{\alpha}$	1.11	(0.0000)	(0.2290)	0.98	2.11	(0.5727)	0.11	0.00
$\boldsymbol{\alpha_i}$								
Canada	0.60	(0.1306)	(0.3268)					0.00
France	1.17	(0.0000)	(0.0626)					-0.17
Germany	0.74	(0.0000)	(0.0282)					0.36
Italy	1.25	(0.0000)	(0.0000)					-0.25
Japan	-0.25	(0.9344)	NA					NA
UK	0.89	(0.0000)	(0.4440)					0.00
US	0.56	(0.0000)	(0.0002)					0.45
$\bar{R}^2$	0.99							
DW	2.32							
σ	0.11							
J P value	(0.6050)							

- $A_t$is aggregate TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- Estimation method is White cross-section standard errors & covariance with number of degrees of freedom correction.
- The Wald statistic tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan's estimate is statistically equal to zero.

Table (3) – 2SLS Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 7
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on an Aggregate Measure TFP
The instruments include the logs of the age distribution, population age 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, and 60-64 by country, and a constant.

	Estimate	P value	Wald	R^2	DW	J P value	σ	Implied β
$\boldsymbol{\alpha}$	1.15	(0.0000)	(0.0003)	0.99	2.11	(0.1476)	0.11	-0.14
$\boldsymbol{\alpha_i}$								
Canada	0.95	(0.0020)	(0.8809)					0.00
France	1.20	(0.0000)	(0.0068)					-0.20
Germany	0.66	(0.0000)	(0.0031)					0.43
Italy	1.20	(0.0000)	(0.0000)					-0.20
Japan	0.07	(0.9441)	NA					NA
UK	1.35	(0.0000)	(0.2537)					0.00
US	0.83	(0.0000)	(0.4020)					0.00
$\bar{R}^2$	0.98							
DW	2.56							
σ	0.11							
J P value	(0.8585)							

- $A_t$is aggregate TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- Estimation method is White cross-section standard errors & covariance with number of degrees of freedom correction.
- The Wald statistic tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan's estimate is statistically equal to zero.

Table (4) – GMM Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 7
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on an Aggregate Measure TFP
The instruments include a constant and two lags of the regressor.

	Estimate	P value	Wald	R^2	DW	J P value	σ	Implied β
$\boldsymbol{\alpha}$	1.03	(0.0000)	(0.5078)	0.98	2.43	(0.8654)	0.11	-0.03
$\boldsymbol{\alpha_i}$								
Canada	0.60	(0.1306)	(0.3268)					0.00
France	1.17	(0.0000)	(0.0626)					-0.17
Germany	0.74	(0.0000)	(0.0282)					0.26
Italy	1.25	(0.0000)	(0.0000)					-0.25
Japan	-0.25	(0.9344)	NA					NA
UK	0.89	(0.0000)	(0.4440)					0.00
US	0.56	(0.0000)	(0.0002)					0.44
$\bar{R}^2$	0.99							
DW	2.32							
σ	0.11							
J P value	(0.6050)							

- $A_t$is aggregate TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- 2SLS instrument weighting matrix. Estimation is linear after one-step weighting matrix and white cross-section standard errors and covariance with degrees of freedom corrections.
- The Wald statistic tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan's estimate is statistically equal to zero.

Table (5) – GMM Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 7
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on an Aggregate Measure TFP
The instruments include the logs of the age distribution, population age 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, and 60-64 by country, and a constant.

	Estimate	P value	Wald	R^2	DW	J P value	σ	Implied β
$\boldsymbol{\alpha}$	1.04	(0.0000)	(0.4959)	0.98	2.41	(1.0000)	0.11	0.00
$\boldsymbol{\alpha_i}$								
Canada	0.95	(0.0012)	(0.8755)					0.00
France	1.21	(0.0000)	(0.0041)					-0.21
Germany	0.66	(0.0000)	(0.0016)					0.34
Italy	1.20	(0.0000)	(0.0000)					-0.20
Japan	NA	NA	NA					NA
UK	1.35	(0.0000)	(0.2284)					0.00
US	0.83	(0.0000)	(0.3812)					0.00
$\bar{R}^2$	0.99							
DW	2.28							
σ	0.11							
J P value	(0.4201)							

- A_t is aggregate TFP measure; h_t is human capital; and L_t is the number of researchers.
- P values are in parentheses.
- 2SLS instrument weighting matrix. Estimation is linear after one-step weighting matrix and white cross-section standard errors and covariance with degrees of freedom corrections.
- The Wald statistic tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The J statistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan's estimate is statistically equal to zero.

Table (6) –EGLS Estimates of the G6 Pooled Time Series – Cross Section Data
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on a Market Measure of TFP

	Estimate	P Value	Wald	R^2	DW	σ	Implied β
$\boldsymbol{\alpha}$	1.17	(0.0000)	(0.0000)	0.99	1.74	0.03	-0.17
$\boldsymbol{\alpha_i}$							
France	1.25	(0.0000)	(0.0000)				-0.25
Germany	1.05	(0.0000)	(0.0048)				-0.05
Italy	1.15	(0.0000)	(0.0000)				-0.15
Japan	0.48	(0.1577)	NA				NA
U.K.	1.28	(0.0000)	(0.0004)				-0.28
U.S.	1.23	(0.0000)	(0.0000)				-0.23
$\bar{R}^2$	0.99						
DW	2.15						
σ	0.03						

- $A_t$is TFP market measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- Linear estimation after one-step weighting matrix, white cross-section standard errors & covariance matrix with a degree of freedom correction.
- The Wald statistic tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- Japan is insignificant.
- The U.S. sample is 2000-2014.

Table (7) – 2SLS Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 6
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on a Market Measure TFP
The instruments include a constant, and lags of the regressor

	Estimate	P value	Wald	R^2	DW	σ	J	Implied β
$\boldsymbol{\alpha}$	1.18	(0.0000)	(0.0000)	0.99	1.84	0.03	(0.1053)	-0.18
$\boldsymbol{\alpha_i}$								
Canada	-							
France	1.27	(0.0000)	(0.0000)					-0.27
Germany	1.03	(0.0000)	(0.2482)					0.00
Italy	1.15	(0.0000)	(0.0000)					-0.15
Japan	0.66	(0.1418)	NA					NA
U.K.	1.45	(0.0000)	(0.0067)					-0.45
U.S.	1.23	(0.0000)	(0.0158)					-0.23
$\bar{R}^2$	0.99							
DW	2.24							
J P Value	(0.5269)							
σ	0.03							

- $A_t$is a market TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- Linear estimation after one step weighting matrix. Cross section weights and white cross section standard errors & covariance with degree of freedom correction.
- The Wald statistic tests $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan is insignificant.
- The U.S. sample is 2000-2014.

Table (8) – 2SLS Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 6
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on a Market Measure TFP
The instruments include a constant and the population distribution, age (15-19), (20-24) … (60-64) year

	Estimate	P value	Wald	R^2	DW	σ	JP Value	Implied β
$\boldsymbol{\alpha}$	1.18	(0.0000)	(0.0000)	0.99	1.74	0.03	(0.0859)	-0.18
$\boldsymbol{\alpha_i}$								
Canada	-	-	-	-	-	-	-	-
France	1.25	(0.0000)	(0.0000)					-0.25
Germany	1.05	(0.0000)	(0.0082)					-0.05
Italy	1.15	(0.0000)	(0.0000)					-0.15
Japan	0.36	(0.3866)	NA					NA
U.K.	1.29	(0.0000)	(0.0004)					-0.29
U.S.	1.23	(0.0000)	(0.0000)					-0/23
$\bar{R}^2$	0.99							
DW	2.16							
J P Value	(0.2310)							
σ	0.03							

- $A_t$is a market TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- P values are in parentheses.
- Linear estimation after one step weighting matrix. Cross section weights and white cross section standard errors and covariance with degree of freedom correction.
- Wald is the P value are for testing $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan is insignificant.
- The U.S. sample is 2000-2014.

Table (9) – GMM Estimates of Pooled Time Series – Cross Section Data
Sample (2000-2017) × 6
$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}, u_{it} = \eta_i + v_{it}$
The Dependent Variable is based on a Market Measure TFP
The instruments include a constant and lagged regressor

	Estimate	P value	Wald	R^2	DW	σ	JP Value	Implied β
$\boldsymbol{\alpha}$	1.18	(0.0000)	(0.0000)	0.99	1.73	0.03	(0.9479)	-0.18
$\boldsymbol{\alpha_i}$								
Canada	-	-	-	-	-	-	-	-
France	1.27	(0.0000)	(0.0000)					-0.27
Germany	1.03	(0.0000)	(0.1153)					0.00
Italy	1.15	(0.0000)	(0.0000)					-0.15
Japan	0.13	(0.8742)	NA					NA
U.K.	1.35	(0.0000)	(0.0021)					-0.35
U.S.	1.29	(0.0000)	(0.0000)					-0.29
$\bar{R}^2$	0.99							
DW	2.18							
JP Value	(0.6929)							
σ	0.03							

- $A_t$is a market TFP measure; h_t is human capital; and $L_t$is the number of researchers.
- The instruments are 2 lags of the regressor and a constant.
- 2SLS instrument weighting matrix; linear estimation after one-step weighting matrix; and white cross-section & covariance with degree of freedom corrections.
- P values are in parentheses.
- Wald is the P value are for testing $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan is insignificant.
- The U.S. sample is 2000-2014.

Table (10) – GMM Estimates of the G6 Pooled Time Series – Cross Section Data *

$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}$, $u_{it} = \eta_i + v_{it}$

The Dependent Variable is based on a Market Measure of TFP

The instruments include the logs of the age distribution, population age 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, and 60-64 years by country, and a constant.

	Estimate	P Value	Wald	R^2	DW	J P value	σ	Implied β
α	1.18	(0.0000)	(0.0000)	0.99	1.74	(0.0859)	0.03	-0.18
$\boldsymbol{\alpha_i}$								
France	1.25	(0.0000)	(0.0000)					-0.25
Germany	1.05	(0.0000)	(0.0065)					-0.05
Italy	1.15	(0.0000)	(0.0000)					-0.15
Japan	0.60	(0.1101)	NA					NA
U.K.	1.31	(0.0000)	(0.0004)					-0.31
U.S.	1.24	(0.0000)	(0.0000)					-0.24
$\bar{R}^2$	0.99							
DW	2.15							
J P value	(0.2310)							
σ	0.03							

- A_t is TFP market measure; h_t is human capital; and L_t is the number of researchers.
- P values are in parentheses.
- Estimation method is GMM-EGLS with cross-section weights. Periods included are 17. Cross sections included are 6. Total panel (unbalanced) 99. 2SLS instrument weighting matrix. Estimation is linear after one-step weighting matrix and white cross-section standard errors and covariance with degrees of freedom corrections.
- Wald is the P value are for testing $H_0: \alpha = 1$. It is distributed $\chi^2_{0.95,1}$.
- The Jstatistic tests the null hypothesis of instruments' over-identification restrictions.
- Japan is insignificant.
- The U.S. sample is 2000-2014.

Table (11) – Summary of the Estimated α and implied β
using the Aggregate TFP Measure
$$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}\ ,\ u_{it} = \eta_i + v_{it}$$

	EGLS	implied β	2SLS i	Impliedβ	2SL2 ii	Impliedβ	GMM i	Impliedβ	GMM ii	Impliedβ
α	1.15	-0.15	1.11	-0.11	1.15	-0.15	1.03	-0.03	1.04	-0.04
α_i										
Canada	0.96	0.04	0.60	0.4	0.95	0.05	0.60	0.4	0.95	0.05
France	1.21	-0.21	1.17	-0.17	1.20	-0.2	1.17	-0.17	1.21	-0.21
Germany	0.67	0.33	0.74	0.26	0.66	0.34	0.74	0.26	0.66	0.34
Italy	1.20	-0.2	1.25	-0.25	1.20	-0.2	1.25	-0.25	1.20	-0.2
Japan	0.26	0.74	-0.25	1.25	0.07	0.93	-0.25	1.25	NA	NA
U.K.	1.35	-0.35	0.89	0.11	1.35	-0.35	0.89	0.11	1.35	-0.35
U.S.	0.84	0.16	0.56	0.44	0.83	0.17	0.56	0.44	0.83	0.17

(i) The instruments are lags of the regressor.
(ii) The instruments are the population distribution, age 15-19, 20-24…60-64 year.

Table (12)- Summary of the Estimated α and implied β
using the Market TFP
$$\Delta lnA_{it} - lnL_{it} = \alpha(lnh_{it} - lnL_{it}) + u_{it}\ ,\ u_{it} = \eta_i + v_{it}$$

α	EGLS	Implied	2SLS i	Implied	2SLSii	Implied	GMM i	Implied	GMM ii	Implied
α_i	1.17	-0.17	1.18	-0.18	1.18	-0.18	1.18	-0.18	1.18	-0.18
Canada	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
France	1.25	-0.25	1.27	-0.27	1.25	-0.25	1.27	-0.27	1.25	-0.25
Germany	1.05	-0.05	1.03	-0.03	1.05	-0.05	1.03	-0.03	1.05	-0.05
Italy	1.15	-0.15	1.15	-0.15	1.15	-0.15	1.15	-0.15	1.15	-0.15
Japan	0.48	NA	0.66	NA	0.36	NA	0.13	NA	0.60	NA
U.K.	1.28	-0.28	1.45	-0.45	1.29	-0.29	1.35	-0.35	1.31	-0.31
U.S.	1.23	-0.23	1.23	-0.23	1.23	-0.23	1.29	-0.29	1.24	-0.24

(i) The instruments are lags of the regressor.
(ii) The instruments are the population distribution, age 15-19, 20-24…60-64 year.

Figure (1)
The Stock of Human Capital

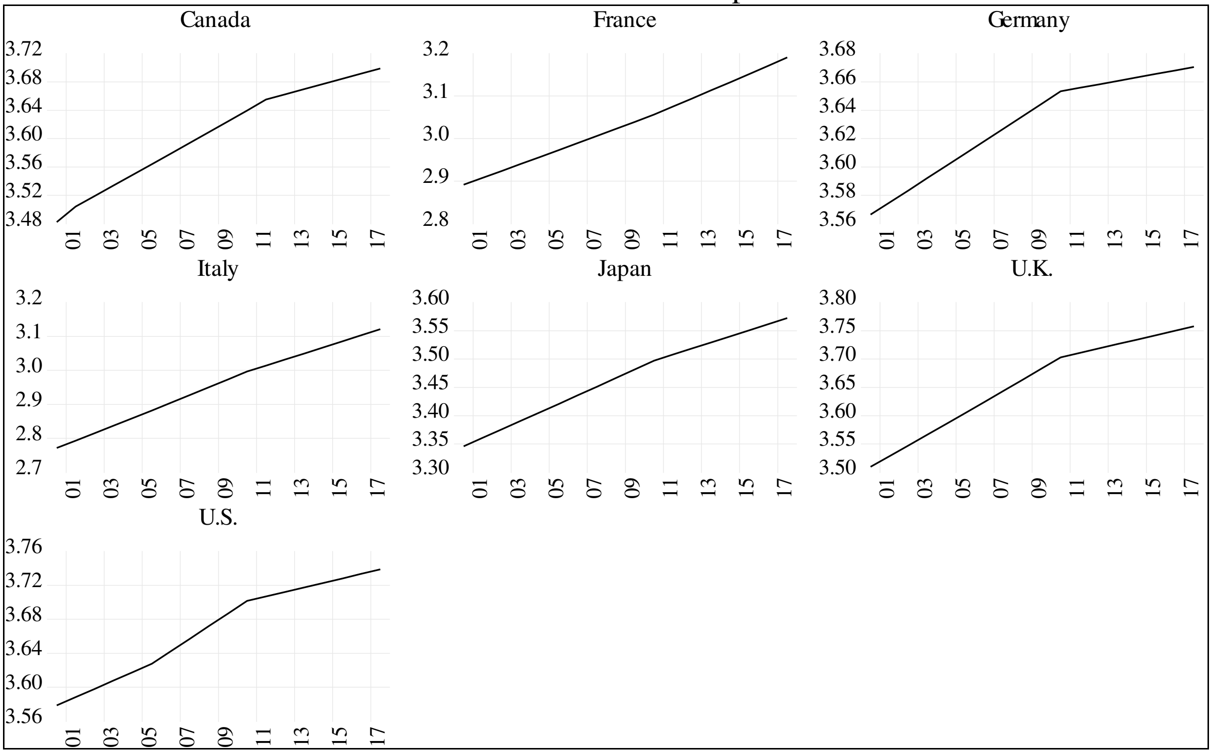


Figure (2)
The Number of Researchers

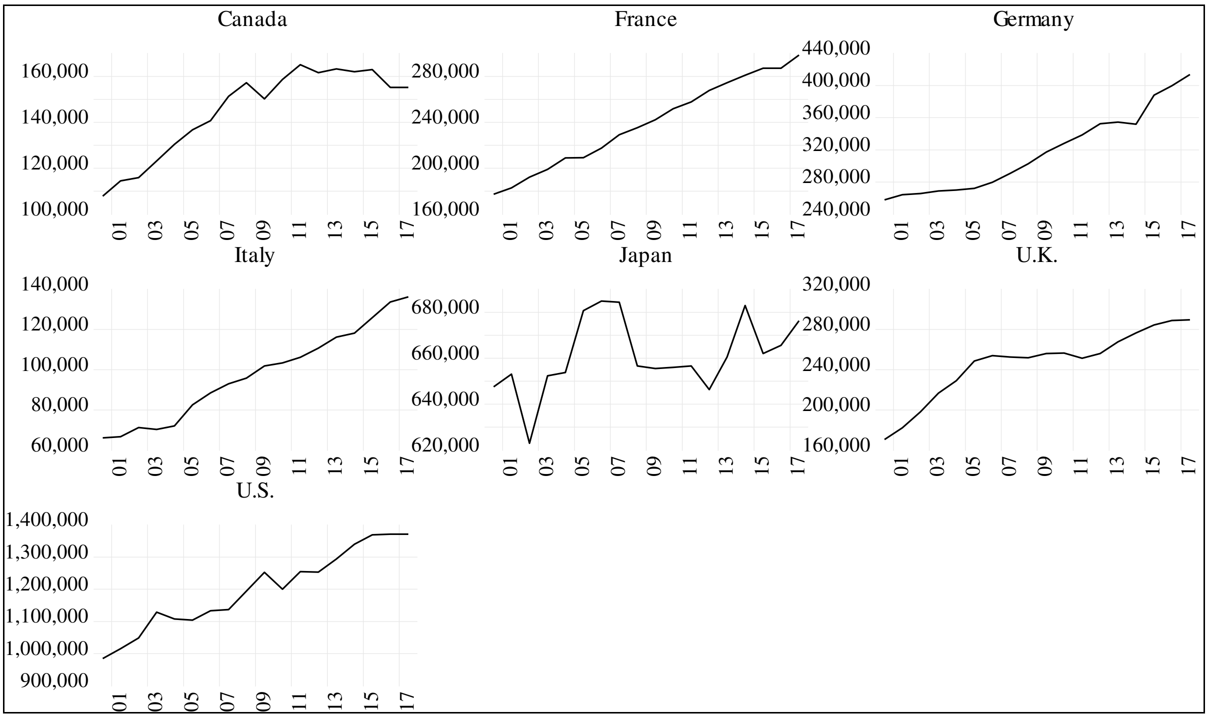


Figure (3)

Aggregate and Market TFP

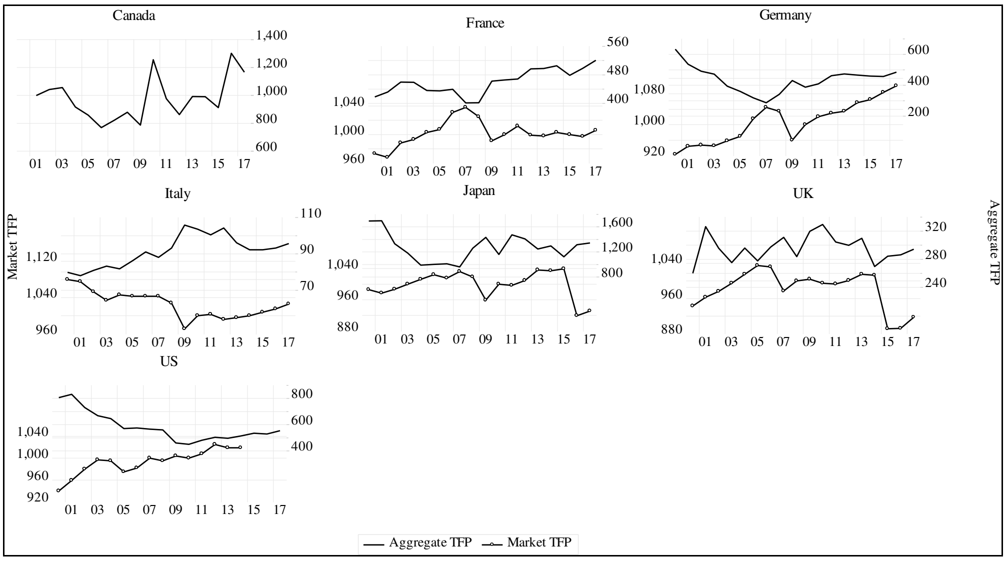


Figure (4)
Aggregate Measure of TFP Growth and Human Capital Level per Researcher

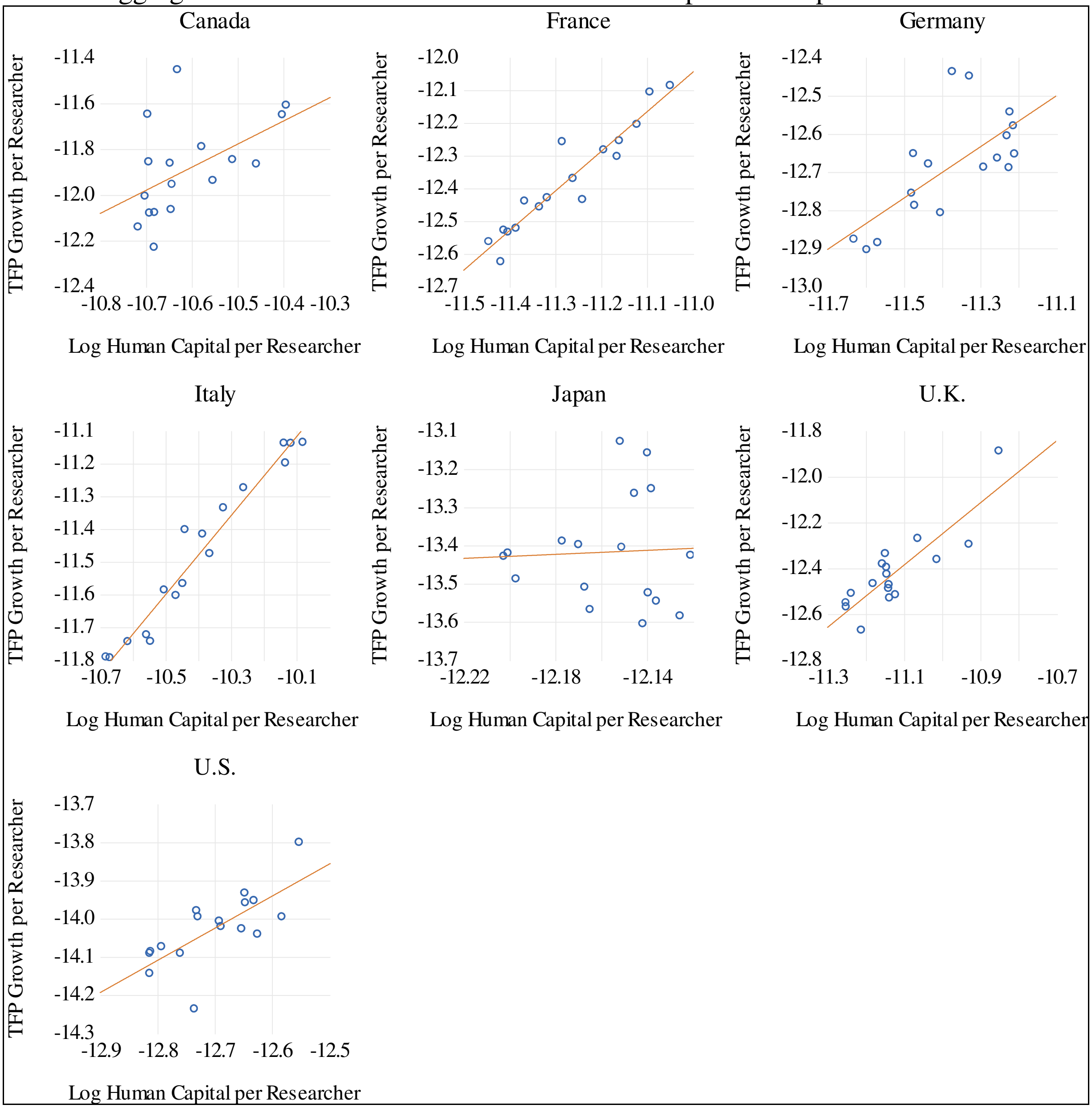
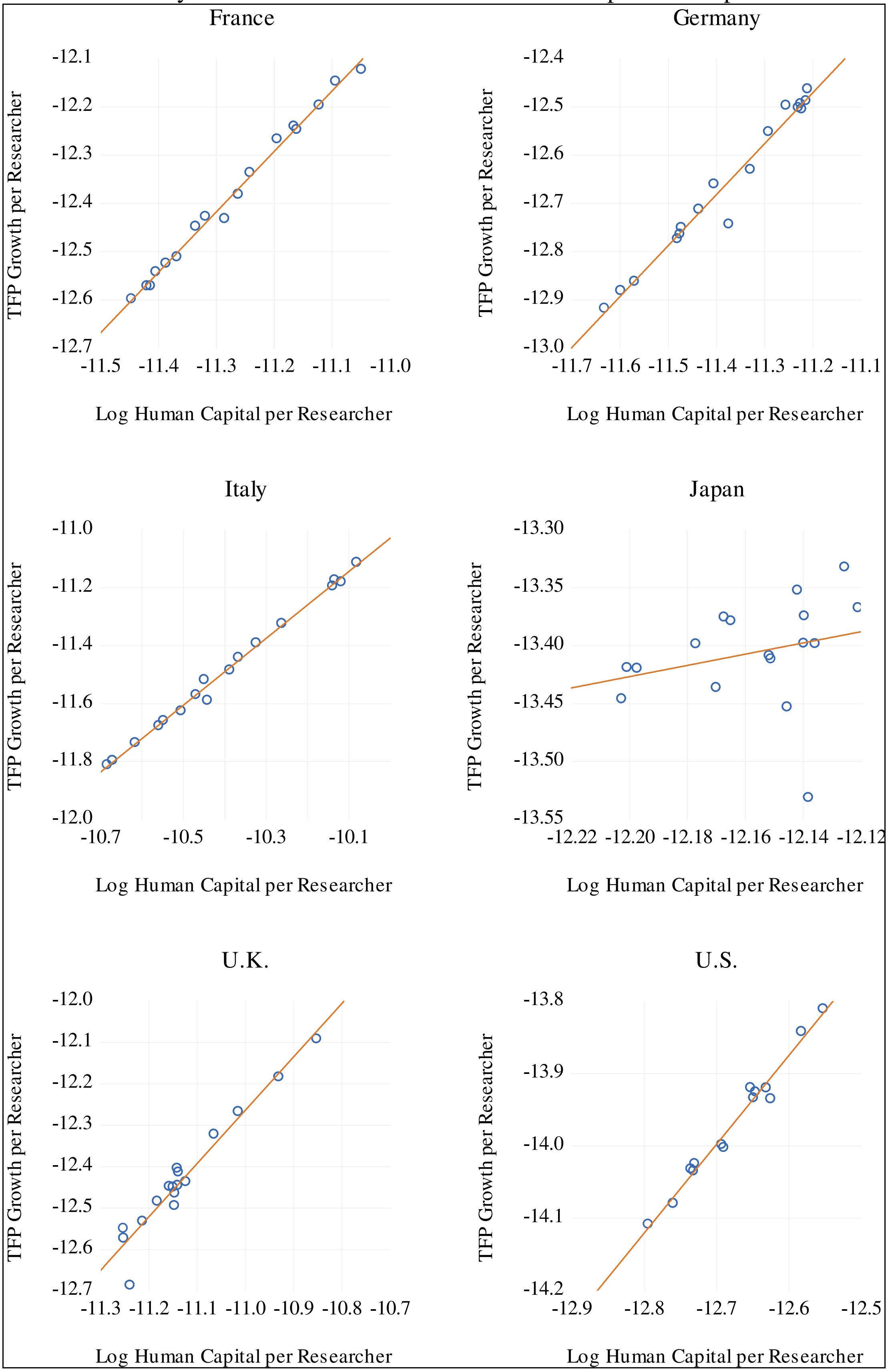


Figure (5)

Market Economy Measure of TFP Growth and Human Capital Level per Researcher



Data appendix

The sample is 2000 to 2017. Human capital – source Penn World Table 9.1, the data of the number of researchers are from the World Bank data set. Researchers are professionals who conduct research and improve or develop concepts, theories, models, techniques instrumentation, and software of operational methods. R&D covers basic research, applied research, and experimental development. We use total population data to obtain the number of researchers.

Total population data are from the Penn World Table 9.1 to convert researchers per million people into an absolute number of researchers. TFP growth rate is from the Conference Board. TFP market measure is taken from EUKLEMS (2000-2017) except for the U.S., where the sample is 2000-2014 for the market economy TFP measure. The Market Economy measure excludes lines L, O, P, Q, T, and U from the data set, which are the sectors real estate activity; Public administration and defense; compulsory social security; Education, Health and Social Work; and Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use.

The population distribution is from the World Bank Development Indicators.

Acknowledgment

I thank John Seater for his insights, constructive comments, and rigorous discussion. I also thank two anonymous referees for their comments.

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[i] See Romer (1990), Aghion and Howitt (1992), Akcigit et al. (2016), for examples of endogenous growth models.

[ii] Typically, human capital is measured by average years of schooling and returns on education, Mincer (1974). See, Bils, and Klein (2000) for example. Human capital level h_t is $e^{\psi l_{ht}}$, where $\psi > 0$. This equation is consistent with Mincer (1974), and Bils and Klein (2000) in the sense that human capital data are based on average years of schooling and the rate of return on education ψ.

[iii] Phelps (1966, pp.133-134) argues that research is an increasing function of the level of technology. Nelson and Phelps (1966, pp.70) hypothesize that educated people make good innovators, and education speeds up the process of technological diffusion. The literature on knowledge and innovation has expanded recently to include different fields beyond economics. See Etzkowitz and Leydesdorff (1995, 2000) who introduced the Triple

Helix model of innovation. The triple helix model of innovation refers to a set of interactions between academia, industry and government, to advance economic and social development, as described in concepts such as the knowledge economy. In addition, see Carayannis and Campbell (2006, 2011) who emphasized diverse knowledge and innovation modes, together with mutual cross learning between knowledge modes and inter-disciplinary and trans-disciplinary knowledge. There could be some implications for enhancing the quality of human capital needed for research effort, and finally economic growth.

[iv] We use a 95% Chi-Squared test for correlation.

[v] We have estimated equation (3) for each country individually from 2000 to 2017 using OLS, 2SLS, and GMM. We do not report these regressions because of the small sample bias. Therefore, the individual country time series estimates could be uninformative.

[vi] We use a 95% Chi-Squared test for correlation.